A Systematic Review of Predictive Maintenance and Production Scheduling Methodologies with PRISMA Approach

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Abstract
Predictive maintenance has been considered fundamental in the industrial applications in the last few years. It contributes to improve reliability, availability, and maintainability of the systems and to avoid breakdowns. These breakdowns could potentially lead to system shutdowns and to decrease the production efficiency of the manufacturing plants. The present article aims to study how predictive maintenance could be planed into the production scheduling, through a systematic review of literature. . The review includes the research articles published in international journals indexed in the Scopus database. 165 research articles were included in the search using #predictive maintenance# AND #production scheduling#. Press articles, conference and non-English papers are not considered in this study. After careful evaluation of each study for its purpose and scope, 50 research articles are selected for this review by following the 2020 Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA) statement. A benchmarking of predictive maintenance methods was used to understand the parameters that contributed to improve the production scheduling. The results of the comparative analysis highlight that artificial intelligence is a promising tool to anticipate breakdowns. An additional impression of this study is that each equipment has its own parameters that have to be collected, monitored and analyzed.
Keywords:
Predictive maintenance; production scheduling; systematic review; PRISMA.

1. Introduction

Nowadays, in modern times, one of the primary objectives and aspirations of every production plant is to achieve and maintain prosperity and success. The maintenance department, being an integral and indispensable component of the overall operation and functioning of any prosperous and thriving business enterprise, plays a crucial and pivotal role. Despite the fact that the maintenance department may not directly contribute to the productive output or yield of the plant, its significance and importance in the overall scheme of things cannot be overstated. In fact, it is one of the most vital and critical departments within the production plant, responsible for striving and endeavoring to maximize the availability and operational efficiency of the equipment and machinery. The primary goal and objective of the maintenance department is to ensure that the machines and equipment are continuously and consistently operational, thereby minimizing the occurrence and frequency of failures and production interruptions. In order to achieve this objective, it is imperative and essential for the maintenance department to promptly and expeditiously address and resolve any and every problem or issue that arises, so as to minimize and mitigate the losses and damages incurred due to equipment shutdowns and also prevent such occurrences from happening in the future.

The fundamental and overarching purpose of maintenance is to uphold and preserve the optimal and desired condition of the equipment and machinery throughout its entire operational cycle, ensuring that it remains functional and capable of performing the required and designated functions and tasks. The key and fundamental principle underlying the proper and effective execution of maintenance activities is to ensure that they are properly defined, meticulously planned, and duly accepted by all relevant stakeholders. These maintenance activities encompass a wide and diverse range of aspects and considerations, including but not limited to product quality, equipment usability, cost reduction, safety, and environmental protection. By adhering and adhering to these maintenance activities, the maintenance department can ensure and guarantee that the machines and equipment are kept in optimal and excellent working condition, thereby facilitating their safe, efficient, and reliable operation. In essence, the primary aim and objective of this research is to explore and investigate the myriad benefits and advantages of predictive maintenance in the context of production scheduling. In line with this research inquiry and objective, the systematic literature review conducted

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as part of this research aimed to identify, evaluate, and synthesize the existing body of knowledge and evidence pertaining to the application and implementation of predictive maintenance in the realm of production scheduling. Consequently, this paper aims to comprehensively and comprehensively present and elucidate the concepts and principles of predictive maintenance and production scheduling. To achieve this aim, the paper has been structured and organized into six distinct sections. The subsequent section will delve into the foundational and fundamental aspects of production scheduling and predictive maintenance, providing a comprehensive explanation and overview of these concepts. Section 3 will detail and outline the materials and methods employed in conducting this research. The findings and outcomes of the systematic literature review will be expounded and presented in section 4. Finally, section 6 will culminate and conclude the study, summarizing the key findings and implications thereof.

2. Fundamentals of production scheduling and predictive maintenance

Industrial systems have experienced significant transformations in recent years, necessitating a corresponding evolution in maintenance strategies toward increased efficiency and sophistication. These advancements, however, come with challenges, particularly in managing the usage time of increasingly expensive machines. The extensive utilization of resources can accelerate their health deterioration, ultimately resulting in breakdowns. Consequently, there is a pressing need to develop decision support tools that facilitate the optimized management of machine usage. In this section, we provide clear definitions of production scheduling and predictive maintenance, elucidating the potential impact of predictive maintenance on production scheduling.

2.1 Production Scheduling

Production scheduling is a crucial decision-making process that facilitates the efficient organization of production resources within a company. Positioned as a key step in the planning process, it integrates essential factors in the production system, including customer demands, production planning, and resource allocation (refer to Figure 1). Scheduling, widely applicable in various industries, particularly in manufacturing and services, involves allocating existing production resources, such as machines, to execute a sequence of tasks or jobs within a specified timeframe. The primary objective is to meet performance criteria, encompassing both customer satisfaction and production efficiency [2].

In today's production systems, the pursuit of increased productivity and optimized average costs requires the development of flexible scheduling systems capable of adapting to changes and minimizing downtime. Production systems encounter challenges such as unpredictable customer demands, machine breakdowns, and delivery delays, imposing significant constraints. As a result, production management extends beyond its core objective of goods production to address secondary objectives, categorized as external objectives related to customer satisfaction and internal objectives linked to optimizing the production system's use.

Effective scheduling plays a pivotal role in improving both external and internal objectives, positioning production scheduling as a extensively researched topic in operations research, management science, and artificial intelligence, all aimed at enhancing production efficiency.

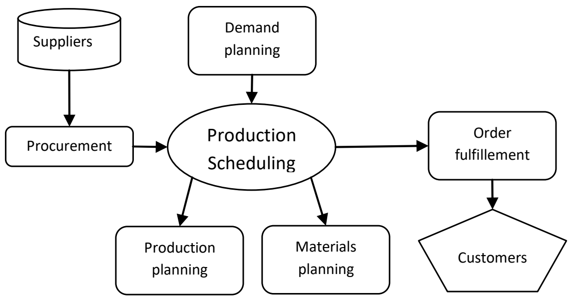

Fig. 1. A summary of production planning and control activities in a company [1].

There are various types of production scheduling, each suited to different manufacturing scenarios. These include production within a single machine, parallel machines, and job production scheduling, further categorized into flow shop, open shop, and job shop [3]. In flow shop scheduling, jobs follow a predetermined sequence of operations, ideal for highly standardized assembly line production [1]. Open shop scheduling is similar, but with no specific ordering constraints on operations. Job shop scheduling (JSS) deals with jobs having ordered lists of operations, and it's a challenging problem in combinatorial optimization, often considered NP-hard [4]. Job shops, prevalent in businesses with complete customization, pose complexity due to varied production processes for each job, resulting in unique finished products [1]. JSS can be classified based on job information availability, distinguishing between static (classical) JSS and dynamic JSS [5]. Additionally, depending on whether a job can be processed on more than one machine, JSS is categorized into flexible JSS and non-flexible JSS [6].

2.2 Predictive Maintenance

Predictive Maintenance (PdM) employs advanced tools to determine the optimal timing for maintenance actions [7]. This approach relies on continuous monitoring of machine or process integrity, allowing for maintenance only when necessary [8]. It also facilitates early failure detection through predictive tools utilizing historical data (e.g., machine learning techniques), integrity factors (e.g., visual aspects, wear, discoloration differing from the original), statistical inference methods, and engineering approaches [8].

PdM revolves around real-time monitoring and diagnosis of system components, processes, and production chains [9]. The core strategy involves taking action when items or parts display behaviors indicative of potential machine failure, degraded performance, or a decline in product quality. Initially driven by system checks at predetermined intervals, preventive maintenance focused on analyzing the health of equipment, machines, or components within machinery [10]. In recent years, PdM has found applications in various domains, including (cyber) security issues, infrastructure management, energy fabrication, power plants, maritime systems, exploitation facilities, as well as in production chains or in future factories [11].

Essentially, predictive maintenance is a philosophy that optimizes total plant operation by utilizing the actual operating condition of plant equipment and systems. A comprehensive predictive maintenance management program utilizes cost-effective tools (e.g., vibration monitoring, thermography, tribology) to acquire real-time data and schedules maintenance activities based on actual needs [12]. The integration of predictive maintenance in a comprehensive maintenance management program optimizes process machinery availability, significantly reduces maintenance costs, and enhances product quality, productivity, and profitability in manufacturing and production plants [12].

2.3 Predictive Maintenance Integrated into Production Scheduling

In the management of production and maintenance during disturbance conditions, three distinct approaches are employed: predictive, proactive, and reactive (refer to Figure 2) [13]. The goal of the predictive approach is to formulate a schedule capable of absorbing disturbances without affecting planned external activities, all while maintaining heightened system efficiency.

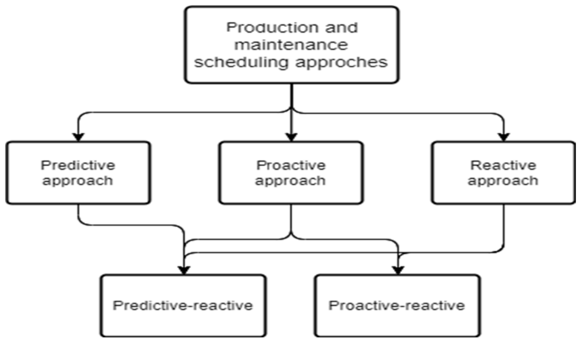

Fig. 2. Classification of Production and Maintenance Scheduling Approaches [13].

By foreseeing future machine conditions and assessing the health states of machines before executing a production schedule, plant decision-makers can proactively prevent failures attributed to machine degradation, subsequently enhancing the overall cost-effectiveness of the manufacturing system [14]. The joint optimization of job operations and Predictive Maintenance (PdM) actions results in improved planning and increased efficiency.

3. Literature review of predictive maintenance integrated into production scheduling

The Systematic Literature Review (SLR) is a well-acknowledged approach utilized to discover, evaluate, and interpret pertinent research on a particular subject, domain, or phenomenon [15]. Functioning as a supplementary examination, SLR strives to review studies with comparable objectives, rigorously assess methodologies, and consolidate results for statistical or meta-analysis when applicable

[8]. In order to improve reporting transparency and consistency, the Quality Of Reporting Of Meta-analyses (QUOROM) guidelines were initially created and subsequently refined through the PRISMA statement [16].

3.1 Literature Review According to PRISMA Guidelines

The PRISMA 2020 statement is primarily crafted for systematic reviews examining the effects of health interventions, regardless of study design [17]. Despite its health focus, the checklist items are versatile and can be applied to systematic reviews evaluating various interventions like social or educational interventions. These guidelines are relevant not only for reviews centered on intervention assessment but also for those with broader objectives, such as examining prevalence or prognosis [16]. PRISMA 2020 is suitable for systematic reviews with or without synthesis, encompassing mixed-methods reviews that integrate both quantitative and qualitative studies. While it emphasizes original and updated systematic reviews, PRISMA 2020 is also pertinent to continuously updated ("living") systematic reviews [17].

This updated statement empowers academic authors to efficiently construct comprehensive systematic reviews with significant relevance to the research community. It ensures a thorough understanding of the research topic and facilitates the identification of new questions for future investigation [16, 17, 19].

3.2 Literature Review Planning Protocol

This paper follows a systematic planning protocol for the review, offering a comprehensive framework that serves as a valuable guide for researchers to gain a deeper understanding of the research topic, recognize limitations, and explore future directions for integrating maintenance methods into production scheduling.

Research Questions: The paper addresses two main questions: (1) How are predictive maintenance methods utilized in production scheduling? and (2) In which fields is predictive maintenance widely applied? The selection of papers discussed in this work is based on these key questions.

Databases for Literature Searching: The study utilized Scopus, a reputable scientific literature database. All chosen papers are scientific articles from international journals indexed by Scopus, published in English between 2011 and 2023.

Execution: For the execution of the Systematic Literature Review (SLR), keywords for constructing search strings were selected based on terms commonly found in the literature and terms specific to this review (i.e., Predictive maintenance applied to production scheduling).

The search on Scopus used the formula:

TITLE-ABS-KEY(("predictive maintenance" OR "PdM") AND ("production schedu*" OR "production plan*"))

A total of 165 papers were initially found. After completing the PRISMA process (Figure 3), 50 papers were identified as relevant to this literature review and selected for subsequent analysis. These papers offer insights into predictive maintenance within the context of production scheduling.

4. Results and Discussions

Adhering to the PRISMA guidelines, 50 research papers were identified during the literature review, primarily sourced from journals with an engineering and manufacturing focus.

4.1 Distribution of publications over the year

In Figure 4, the publication trend from 2011 to 2023, complete with a trend line, is evident. This analysis reveals that the incorporation of predictive maintenance into production scheduling has gained attention relatively recently in research. Up until 2017, only four papers were published, indicating a growing interest in this concept. However, there has been a noticeable upswing in research activity post-2017. Specifically, the average number of papers rose from 0.8 articles per year in the period of 2011–2016 to 5.4 articles per year in 2016–2021.

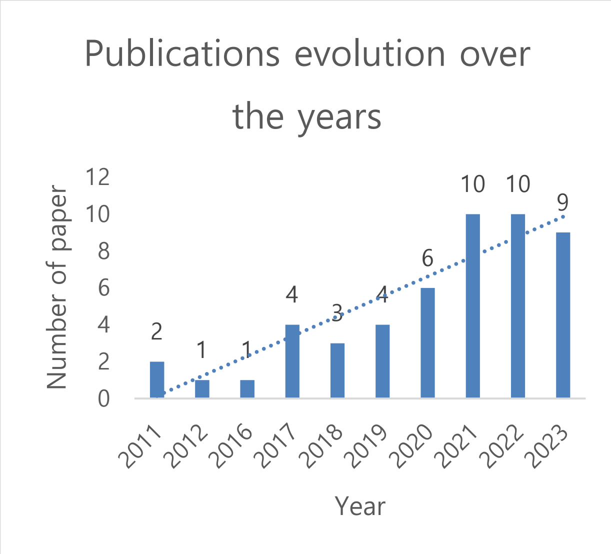

Fig. 5. Journal-wise Article Distribution

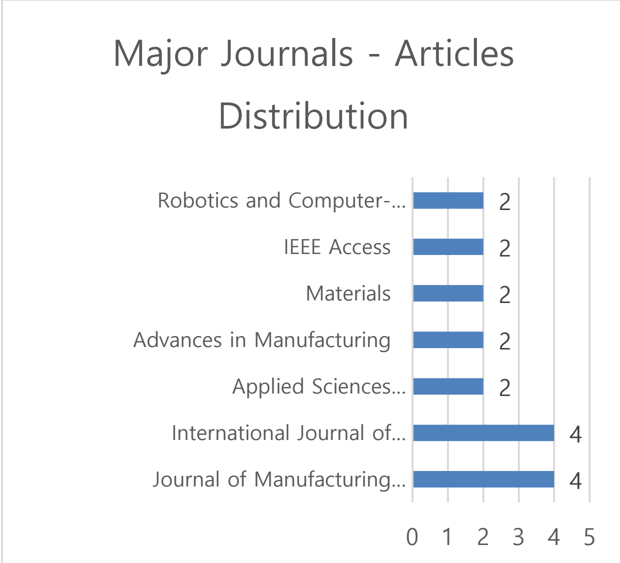

Fig. 6. Highly Cited Articles

The authors in [20] argue that the limited number of works in the PdM domain is attributed to the intricacy of implementing effective PdM strategies in production settings.

4.2 Journal-wise Publication Distribution

The chosen papers, focusing on PDM applied to production scheduling, are dispersed across a diverse set of journals, encompassing a total of 28 journals. Notably, the International Journal of Advanced Manufacturing Technology holds the top position with 3 publications, followed by the Robotics and Computer-Integrated Manufacturing journal with 2 publications. The remaining journals each feature 1 publication (See Figure 5). The distribution includes 28 articles, 2 reviews, and 1 chapter.

4.3 Overview of Highly Referenced Articles:

Examining the topic in question, the most referenced articles (refer to Figure 6) are succinctly summarized. Leading the citation count is the research paper titled "Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison," boasting 421 citations. Following closely is the article on "Single-machine-based joint optimization of predictive maintenance planning and production scheduling" with 72 citations, while the remaining articles have garnered fewer than 46 citations each.

4.4 Analysis of Research Methods:

Table 1 presents our analyses of eligible articles, offering an insight into the most recent papers on PdM and production scheduling. Each line corresponds to a specific paper, with the first three columns detailing its reference, method employed, and equipment used. The fourth column provides a description of the data applied for prediction, while the fifth column, labeled "Data type," indicates whether Real Data (RD) or Synthetic Data (SD) was used in the study case. "NA" denotes not applicable.

TABLE I. ANALYSE OF READE ARTICLES

Reference	**Used Methods**	**Equipment**	**Description of the data applied for predictive maintenance**	**Data type**
[21]	Machine learning	Wear on a brake system	Braking force Brake pads thickness	RD
[22]	Ant colony optimization	FDM (Fused Deposition Molding)	Data on the environment FDM machine generated data	RD
[23]	Artificial Intelligence	Photovoltaic cells	Electrical signals	RD
[24]	Mathematical Model	Micro Gas Turbines	Sensors measurement	SD
[25]	Hybrid metaheuristic	Industrial equipment	Prognostics and Health management (PHM) Signals	SD
[26]	Artificial Intelligence	Production chains	Key Indicator Performance results	RD
[13]	Ant colony optimization	-	Reliability characteristics	SD
[27]	Mathematical Model	Electric steering gears	Reliability characteristics	RD
[28]	Deep learning model	Machine Speed Direction	Historical data	RD
[29]	Big data and Machine learning	NA	MES Manufacturing Execution System & Signals data	SD
[30]	Online measuring device	5axis CNC milling machine	Sensors data	RD
[31]	Genetic Algorithm	NA	Repair procedure ; Design parameters	SD
[32]	Mathematical model	Gas compression system	Historical maintenance data ; Sensors data	RD
[33]	Agglomerative hierarchical clustering algorithm	CNC Computer Numerical Control	Electrical power	SD
[34]	A predictive association rule-based maintenance policy	Oil refinery	Input parameters	RD
[35]	Genetic Algorithm	Hydraulic Pump Wear	Health state transition probability; Production parameters	RD
[36]	Artificial neural networks	Retrofitted CNC milling machine	Sensor Signal : Vibration data	RD
[37]	Monitoring Model	Bearings	Lubricating oil samples analysis	RD
[38]	Big data	Smart manufacturing	NA	NA
[39]	Deep digital maintenance	Oil cooler	Systems : enterprise resource planning (ERP) & manufacturing execution system (MES)	RD
[40]	Nonlinear optimization	Boring tool	Parameters setting	RD
[50]	-Deep learning and mathematical programming -A long short-term memory model	- N/A	Sensors. Data	RD
[51]	Maintenance driven scheduling cockpit	N/A	N/A	N/A
[52]	- Deep neural networks (DNN) and recurrent neural networks (RNN) models were used. - Regression random forest (RRF) - Job Shop algorithms from Google's OR-Tools	N/A	Sensor telemetry and operating information -	RD
[53]	- Production-inventory model - Quality-maintenance policy - Rework process - Random failures - Multiple assignable causes	N/A	N/A	RD

[54]	Multi-agent system called SCEMP. (Supervisor, Customers, Environment, Maintainers and Producers)	N/A	N/A	SD
[55]	Markov decision model	N/A	IIoT sensors	RD
[56]	- (Log)-location-scale (LLS) regression model - Multivariate functional principal component analysis (MFPCA) - Real-time prognosis updating framework	N/A	Monitoring data	RD
[57]	Advanced signal processing techniques	-Inertial vibrator -Sieving screen - Bearings -Vibrating screen - Accelerometers	Signals of vibration	RD
[58]	- Immune algorithm (IA) and long short-term memory network (LSTM) with attention mechanism lifespan - Linear regression	Digital welding machines.	Degradation characteristic indicators	RD
[59]	N/A	N/A	N/A	N/A
[60]	-Machine learning techniques	- The production line consists of electrical, mechanical, and automated equipment. - The workshop of a raw mill in an Algerian cement plant is selected for the study.		
[61]	N/A	N/A	N/A	N/A
[62]	-Multilayer bidirectional long short-term memory (Bi-LSTM) - Convolutional neural networks -Fusion network	N/A	C-MAPSS dataset.	RD
[63]	Multi-perspective data-oriented services in Cyber-Physical Production Networks	N/A	Cyber Physical Production Network.	RD
[64]	- Multiple linear regression - GRU model	N/A	N/A	RD
[65]	Heuristic algorithm based on Tabu search.	Photolithography machines used by a red electronics manufacturer.	N/A	RD
[66]	- Prognostics and Health Management (PHM) module - Predictive maintenance integrated production scheduling (PdM-IPS) module - Two-stage Genetic Algorithm (TSGA)	N/A	N/A	N/A
[67]	Mathematical models	N/A	Reliability characteristics	N/A

The comprehensive review conducted underscores the widespread application of predictive maintenance across diverse equipment and fields. Notably, a significant observation is the predominant use of real data over synthetic data in the analyzed papers. This trend may stem from the specific characteristics inherent in each predictive maintenance application, where synthetic data might not effectively represent real-world scenarios [8].

Furthermore, Table 1 highlights a clear preference for certain methods, with artificial intelligence, particularly machine learning, being the most frequently employed. Additionally, genetic algorithms and ant colony algorithms emerge as the preferred heuristic search algorithms.

The breakdown of PdM applications in Table 1 reveals a correlation between each application and specific equipment. This equipment spans various domains, including brake systems, molding machines, photovoltaic cells, turbines, electric steering gears, machine speed direction, CNC milling machines, gas compression systems, CNC (Computer Numerical Control), oil refineries, hydraulic pumps, bearings, and oil coolers.

An interesting trend identified in Table 1 is the prevalent use of sensor data to detect anomalies in equipment. Beyond the papers cited in Table 1, additional references [41–49] can be considered to further enrich the categorization by field (See Figure 7).

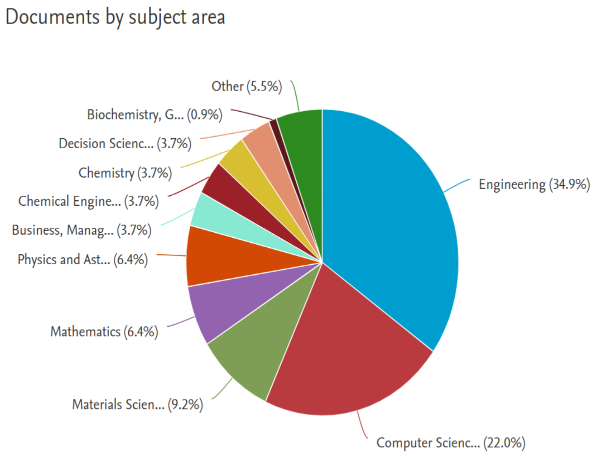

Fig. 7. Research Papers Addressing PDM and Production Scheduling by subject area

The identified papers underwent further scrutiny based on the potential field category impacted. On average, manufacturing systems constituted the majority, accounting for 65% of the papers. Small variances were observed, with smart manufacturing (industry 4.0) and the energy sector each representing a significant portion. Papers focusing on the automotive industry comprised 6% of the research, while both the food industry and additive manufacturing contributed 3% each. The insights gathered from the characteristics of the most recent papers on PdM (Table 1 and Figure 7) contribute to addressing the research questions outlined in Section 3.2.

5. Conclusion

In conclusion, this paper thoroughly explored existing literature, delving into crucial research on Predictive Maintenance (PdM) and production scheduling, addressing outlined research questions following PRISMA 2020 guidelines. The findings emphasized the specificity of each proposed approach to particular equipment, making direct comparisons with other techniques challenging. Notably, PdM emerged as an innovative tool for effectively managing maintenance events, reflecting the evolving landscape within the industrial field.

Within this review, certain efforts utilized standard Machine Learning (ML) methodologies without parameter tuning, relying on sensor-derived data for predictive maintenance. This trend suggests the early stage of PdM exploration in the industrial domain.

A key point is the significance of prior implementation of PdM strategies within a facility's processes to gather essential data for effective modeling. This data-driven approach is crucial for designing and validating a successful PdM strategy, contributing to improved efficiency and reduced downtime.

However, it's important to acknowledge the limitations of this literature review. There are areas within the realms of PdM and production scheduling that require further investigation. Future research endeavors should focus on developing enhanced sensing techniques for equipment to improve both the quantity and quality of data, conducting studies to assess the impact of PdM on product quality, and proposing optimization methods for PdM data analysis. These recommendations aim to contribute to the ongoing advancement of knowledge in the dynamic and evolving field of predictive maintenance in production scheduling.

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